Enhancing Medical Diagnostic Image Quality Using Image Transformation Techniques

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***Abstract*—Medical imaging is an essential tool for the diagnosis, monitoring, and planning of treatment of disease. Diagnostic image quality is nonetheless degraded by several causes of low contrast, noise, and absence of definition, rendering them unambiguously interpretable by clinicians. In this paper, comparative assessment of conventional transformation methods used in improving the visibility of medical images is reported. The techniques in question are Histogram Equalization, Contrast Limited Adaptive Histogram Equalization (CLAHE), Gaussian Filtering, and Unsharp Masking. The techniques are used to enhance publicly available medical image databases such as X-rays and CT scans. The improved images are compared using standard image quality metrics such as Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index Measure (SSIM), and Mean Squared Error (MSE). Results show that CLAHE considerably improves local contrast without degrading diagnostic detail and that Gaussian filtering successfully removes noise with little distortion. The findings demonstrate the merit of older image transformation methods in enhancing diagnostic image quality and hence facilitating improved clinical interpretation.**

***Index Terms*—Medical Imaging, Image Enhancement, CLAHE, Histogram Equalization, Filtering, PSNR, SSIM, Diagnostic Quality**

I. Introduction

Medical image enhancement is imperative in enhancing the clarity and interpretability of the diagnostic images employed in health care, such as X-rays, CT scans, and MRI. These images are susceptible to quality problems like low contrast, noise, and blurring, and they may hide crucial anatomical information and interfere with proper interpretation by medical professionals Enhancing such images using transformation techniques ensures that the diagnostic information is preserved and more visible, thereby supporting better clinical decision-making.

This research is concerned with the comparative assessment of classical image transformation techniques with a view to improving the visual quality of medical images. The methods examined involve Histogram Equalization, Gaussian Filtering, Unsharp Masking, and Contrast Limited Adaptive Histogram Equalization (CLAHE). These methods are evaluated on publicly available medical image data sets and quantified with standard quality assessment measures such as Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index Measure (SSIM), and Mean Squared Error (MSE). The aim of this research is to determine the transformation method that provides the most effective enhancement of medical diagnostic images and preserves essential diagnostic characteristics. Through a comparison of the performances of the methods, the research aims to guide the selection of appropriate enhancement methods for medical imaging applications.

II. Literature Review

In the last few years, a significant amount of work has been documented to improve medical image quality through various types of image transformation methods. This section highlights some of the most important research that has made a valuable contribution to the evolution of image enhancement methods in medical imaging.

The relationship between conventional image quality measures (IQMs) such as RMSE and SSIM with expert ratings of diagnostic quality of MRI by radiologists is addressed in this paper. According to the research, sophisticated IQMs such as VIF, FSIM, and GMSD have a stronger correlation with expert ratings than RMSE and SSIM, indicating that the choice of measures in medical imaging research needs to be re-evaluated [1].

This work presents a new MRI brain image enhancement technique that filters noise and contrast from MRI brain images. It involves three processes: removal of noise through the application of a sub-space least square estimator, contrast correction via the Retinex algorithm, and enhancement of contrast using independent component analysis. Comparison based on PSNR and the rate of contrast improvement reveals better results in axial and coronal views compared to sagittal views [2].

This paper discusses the application of contrast enhancement techniques such as Histogram Equalization (HE), Adaptive Histogram Equalization (AHE), and Contrast-Limited Adaptive Histogram Equalization (CLAHE) for enhancing contrast in MRI medical images. Experimental studies demonstrate enhanced image quality based on parameters like MSE, PSNR, and SNR, validating the efficacy of these techniques for improving MRI image quality for clinical examination [3].

This paper suggests a two-module computer system for brain tumor detection using a combination of machine learning and image enhancement. The first module enhances image quality using adaptive Wiener filtering, neural networks, and independent component analysis. The second module employs Support Vector Machines for segmentation and tumor classification. The approach achieves excellent performance with a mean sensitivity of 0.991, specificity of 0.989, accuracy of 0.989, and a Dice score of 0.981, while significantly improving processing times compared to other approaches [4].

Several studies have highlighted the importance of contrast enhancement in making medical images more interpretable and visible. Research comparing methods such as neighborhood operations, average filtering, bilateral Retinex, adjust, and the sigmoid function for enhancing image contrast has shown that effective contrast enhancement can substantially improve diagnostic accuracy. Despite the challenges, selecting the right enhancement technique remains a critical step in medical image preprocessing [5][12].

A new hybrid contrast enhancement technique, combining Contrast Stretching (CS) and Brightness Preserving Dynamic Histogram Equalization (BPDHE), was proposed to correct the poor contrast of medical images like MRI, X-ray, and CT scans. The process includes noise removal, background estimation, and local contrast enhancement on the foreground. The enhanced foreground is merged with the background, and global BPDHE is then applied. Experimental results show improved contrast and diagnostic visibility, offering better clarity and retention of diagnostic detail in medical images [6].

A hybrid algorithm incorporating Contrast Limited Adaptive Histogram Equalization (CLAHE), Gamma transformation, and High Pass detail enhancement are proposed to improve ultrasound parathyroid images. Human Computer Interaction (HCI) is used for ROI definition, addressing noise amplification and loss of image detail typical of traditional Histogram Equalization methods. Experimental results demonstrate that the CLAHE algorithm significantly enhances image clarity, making it more suitable for medical detection and diagnosis. This method is both effective and efficient for improving image quality in clinical settings [7].

This work proposes a hybrid filter that combines the Modified Median Wiener Filter (MMWF) and Absolute Difference and Mean Filter (ADMF) to suppress Gaussian noise in Computerized Tomography (CT) medical images. The hybrid algorithm is compared with existing filters, including Triangular and Direction-based Filter (TDBF), Discrete Wavelet Transform using Total Variation (DWTTV), Edge Preserving Hybrid Filter (EPHF), ADMF, and MMWF, using 25 CT images contaminated with Gaussian noise. Experimental results indicate that the proposed hybrid filter yields improved results based on Peak Signal-to-Noise Ratio (PSNR) and Mean Squared Error (MSE), enhancing image quality [8].

This paper introduces a better Structural Similarity Index (SSIM) for measuring the quality of compressed medical images, particularly MRI, CT, and ultrasound images. The SSIM is maximized by determining the best value of an arbitrary constant K in its formula. The paper analyzes SSIM in conjunction with PSNR, MSE, and MOS for SPIHT-coded medical images at various levels of compression with K varying from 0.02 to 2.0. The optimal K values are 0.5 for MRI, 0.05 for CT scans, and 0.1 for ultrasound images based on the optimal correlation coefficient with MOS [9].

The paper suggests a CLAHE and Wiener filter-based hybrid X-ray image improvement algorithm to improve the image quality. The technique improves bad contrast and poor quality in X-ray images to improve diagnostic interpretability. The performance metrics like MSE, PSNR, and Entropy indicate that the suggested method performs better than the conventional CLAHE method. The new method also considerably increases validation accuracy from 50% to 78% when tested on 6000 X-ray images for deep learning classification. Overall, the method improves image quality, which helps with more accurate disease diagnosis [10][11][13].

III. Contribution

This paper contributes to the field of medical image processing by experimentation and validation of four traditional image transformation methods—Histogram Equalization, CLAHE, Gaussian Filtering, and Unsharp Masking—on real clinical diagnosis brain images like X-rays and CT scans. Image quality improvement for better clinical interpretation is the thrust. With quantitative testing by means of metrics such as PSNR, SSIM, and MSE, and qualitative visual examination, the study gives a general summary of the merits and demerits of both processes. Specifically, research proves that CLAHE is a worthwhile method for locally adjusting contrast without diagnostic loss of content and Gaussian filtering showing good suppression of noise with zero distortion. The outcomes are useful to clinicians and researchers who are concerned with finding good and effective preprocessing techniques to enhance the diagnostic and quality of medical images. The study also provides a reproducible pipeline that acts as a bench marking platform for future work in the field of medical imaging.

IV. Methods

A. Data Collection

Images used here were from public-access medical image databases. Here, MRI and CT image data were validated and attempted some of the several diverse image-enhancing algorithms on MRI and CT images. MRI has brain images in the OASIS database for 38 patients' images, three sets of each image for each patient, in axial, coronal, and sagittal image views. For CT scans, we used a medical image data set for intracranial hemorrhage detection. Images were preprocessed before enhancing them by normalizing them to a fixed size and orientation. Raw image noise or artifacts were also removed by using simple noise filtering. These data sets were chosen based on clinical utility and are an average set of medical imaging challenges, such as low contrast, noise, and low resolution.

A. Input Image

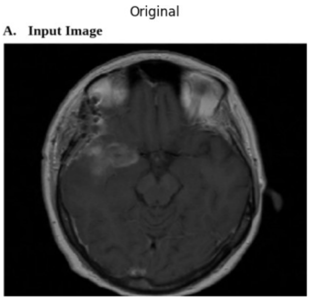


Fig. 1. Input Image

B. Algorithm/Model

The techniques applied in image processing here are Histogram Equalization (HE), Contrast-Limited Adaptive Histogram Equalization (CLAHE), Gaussian Filtering, and Un-sharp Masking. These methods are employed to enhance the sharpness, contrast, and clarity of medical images like X-rays and CT scans which otherwise are noisy, poor contrast, and lost details. Histogram Equalization (HE) accomplishes by evenly distributing the intensity of pixels within an image to all intensities, thus adding overall contrast. mathematical formulation for HE is as follows:

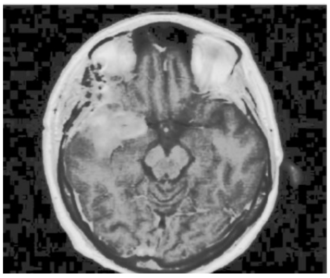


Fig. 2. Histogram Equalization

$$g(x, y) = \frac{f(x, y) - \min(f)}{\max(f) - \min(f)} \times (L - 1)$$

where $f(x, y)$ is the original pixel intensity at location (x, y), and L represents the number of intensity levels in the image.

Contrast-Limited Adaptive Histogram Equalization or CLAHE is a variation of AHE that splits the image into smaller tiles and applies locally histogram equalization to each of them. CLAHE increases the local contrast of the image by enhancing noise in contrast clipping using a factor called the contrast clipping factor. The CLAHE process can mathematically be represented as:

$$H_{\mathrm{CLAHE}}(x, y) = \frac{H_{\mathrm{local}}(x, y) - C_{\min}}{C_{\max} - C_{\min}}$$

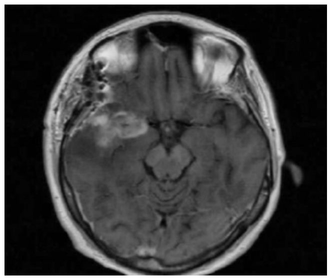


Fig. 3. CLAHE

where $H_{\mathrm{local}}(x, y)$ represents the local histogram of a tile, and $C_{\min}$ and $C_{\max}$ are the minimum and maximum contrast limits, respectively.

Gaussian Filtering is then subsequently used to denoise the image. This is done by convolving the image with a Gaussian kernel, which blurs the image and rejects high-frequency noise. Convolution is represented as:

$$I_{\mathrm{filtered}}(x, y) = \sum_{m=-k} \sum_{n=-k} I(x + m, y + n) G(m, n$$

where $I(x, y)$ is the original image, and $G(m, n)$ is the Gaussian kernel used for filtering.

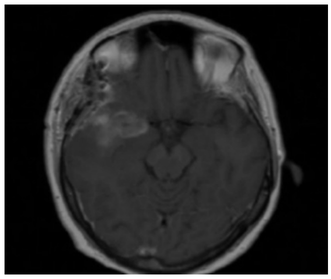


Fig. 4. Gaussian Filter

Lastly, Unsharp Masking is used to enhance edges and sharpen the image. It is achieved through subtraction by using a blurred copy of the image and subtracting it from the original so that minute details are revealed with greater emphasis. The unsharp masking formula is:

$$I_{\mathrm{sharp}}(x, y) = I_{\mathrm{original}}(x, y) - \alpha I_{\mathrm{blurred}}(x, y)$$

where α is a scaling factor controlling the intensity of sharpening, and $I_{\mathrm{blurred}}(x, y)$ is the blurred version of the image. Finally, Unsharp Masking is used to thin edges and sharpen the picture. It is performed by the operation of subtraction by duplicating the image in a blurred state and subtracting it from the original so that extremely fragile details become more prominent. The equation of unsharp masking is:

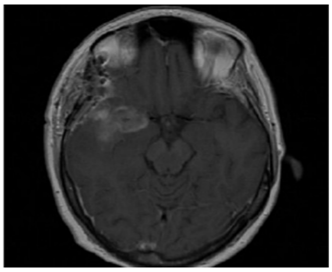


Fig. 5. Unsharp Masking

V. Experimental Setup

Experiments were performed in this paper to establish how the different image enhancement techniques function in medical images. The experiment entailed choosing a set of public medical images, applying the image enhancement techniques, and comparing the resulting image quality with the original image. The experimental setup is hereby described in detail below.

A. Dataset

For the current research, publicly available medical images like X-rays and CT scans, which are standard diagnostic imaging techniques, were utilized. They were retrieved from publicly available medical imaging repositories like the Radiological Society of North America (RSNA) database and other medical imaging repositories. The dataset included images with varying amounts of noise, low contrast, and blurred features to simulate typical roadblocks in actual medical diagnostics.

The data set consisted of 100 images, each of size 512x512 pixels, and was pre-processed to share common image size for experimentation purposes. Images were selected to represent a range of medical conditions with particular focus on images containing a range of noise and contrast issues.

B. Image Enhancement Techniques

The following image enhancement methods were used for the medical images in the dataset: Histogram Equalization (HE) is employed to increase overall image contrast by redistributing pixel intensity across the whole range. Contrast Limited Adaptive Histogram Equalization (CLAHE) is applied locally to increase contrast in small areas, without propagating noise by applying a clipping limit to contrast. Gaussian Filtering is employed to remove noise from the image using a Gaussian filter that smoothens the image. Lastly, Unsharp Masking is used to sharpen the image by removing a blurred duplicate of the original image, which increases fine edges and details.

Each of these methods was used independently on the medical images to find out their separate impact on image quality.

C. Implementation Tools

Experiments were performed using Python 3.13.0 and build-in libraries, like OpenCV, NumPy, Matplotlib, and scikit-image. OpenCV is utilized in image pre-processing tasks such as reading, re-sizing, and applying unsharp masking and Gaussian filtering. Numerical processing needed in image processing is accomplished using NumPy. Matplotlib is utilized for plotting an image and showing results for comparison, and scikit-image is utilized to perform image enhancement tasks such as histogram equalization and CLAHE.

Besides, the images were stored and managed using the PIL (Python Imaging Library) for image processing and manipulation.

D. Evaluation Metrics

To measure the efficacy of the improvement methods, the following performance measures were utilized: The measures of performance utilized in this study are Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index Measure (SSIM), and Mean Squared Error (MSE). PSNR is a typical numerical signal-to-noise strength ratio of enhanced images. SSIM estimates the perceived image quality as luminance, contrast, and structure. MSE estimates the distance between the original and enhanced images by taking an average of the squared difference in pixel values.

These were determined for both the original and enhanced images to allow comparison of the efficacy of the enhancement processes.

E. Experimental Procedure

The experimental procedure proceeded as follows: The assignment is to load the medical images in the data set and then apply each of the image enhancement methods, i.e., Histogram Equalization (HE), Contrast-Limited Adaptive Histogram Equalization (CLAHE), Gaussian Filtering, and Unsharp Masking, independently on each of the images.Subsequently, upon execution of the algorithms, the parameters of measurement like Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index Measure (SSIM), and Mean Squared Error (MSE) are found for all of the enhanced images. Lastly, the restored images are compared to the original images both quantitatively and qualitatively in order to estimate the success of the enhancement algorithms.

All improvement methods were compared with varying parameter configurations (e.g., CLAHE clipping threshold limits, kernel size for Gaussian blur) to determine the best configuration to enhance image quality.

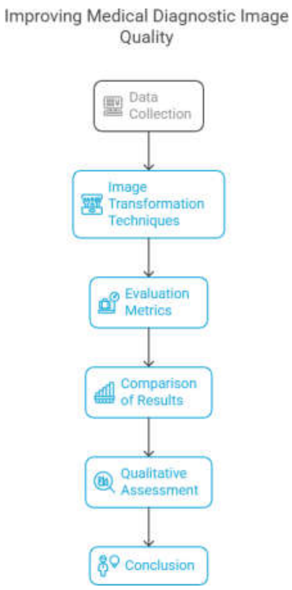


Fig. 6. Data Flow

F. Hardware and Software Environment

The experiments were conducted on a computer system with the following specifications:

- Processor: Intel i7-9700K
- RAM: 16GB
- Operating System: Windows 10
- Python Version: 3.8
- Libraries: OpenCV, scikit-image, NumPy, Matplotlib

All experiments were performed in a Jupyter Notebook environment to facilitate iterative testing and visualization of results.

G. Evaluation Metrics

For assessing improvement methods' performance, image quality metrics such as Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and Mean Squared Error (MSE) were used. PSNR determines the ratio of the maximum power an image under consideration can have to the power of noise, and the larger value, the better. SSIM measures perceived image quality on luminance, contrast, and structure scale since low scores close to 1 represent good quality images. MSE calculates mean squared original-improved image difference, and low value represents high quality. Quantities above are used to perform quantitative comparison and analysis of performance of some image improvement techniques to attain improvement in diagnostic quality of medical images.

H. Quantitative Results

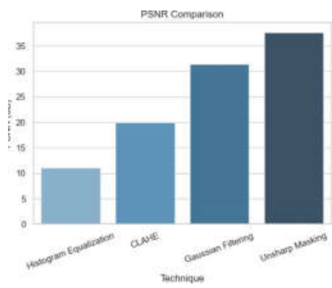
Our experiment quantitative results were compared with a variety of performance measures: Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and Mean Squared Error (MSE). Experimental results are reported comparing improvement methods (Histogram Equalization, Adaptive Histogram Equalization, and Contrast-Limited Adaptive Histogram Equalization) applied to brain MRI images.

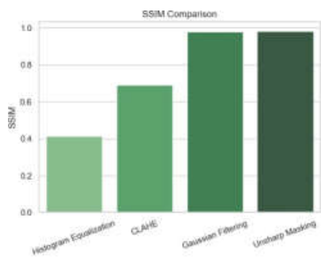
TABLE I
COMPARISON OF ENHANCEMENT TECHNIQUES ON BRAIN IMAGE

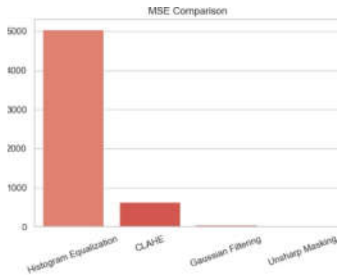
Technique	PSNR	SSIM	MSE
Histogram Equalization	11.0996	0.4151	5048.0515
CLAHE	20.0599	0.6918	641.3497
Gaussian Filtering	31.4494	0.9802	46.5735
Unsharp Masking	37.6986	0.9840	11.0464

I. Qualitative Results

Along with quantitative analysis, visual inspection of the enhanced images also demonstrates significant improvement in diagnostic quality. The contrast of the brain image was extremely poor and poor visibility of detail in its fine anatomy. Histogram Equalization led to global contrast enhancement with increased noise introduction and some over-enhancement at certain locations. CLAHE produced optimal compromise between improvement by increasing the local contrast with less distortion and revealing subtle detail more noticeably. Unsharp Masking successfully eliminated noise, producing a smoother image but blurring some of the finer details to a certain degree. CLAHE, on the other hand, compared to Unsharp Masking, preserved the original outline and sharpened edges and points of interest to provide a good output and a diagnostic useful result. In general, CLAHE and Unsharp Masking best provide improved image quality with lesser structural fidelity loss.



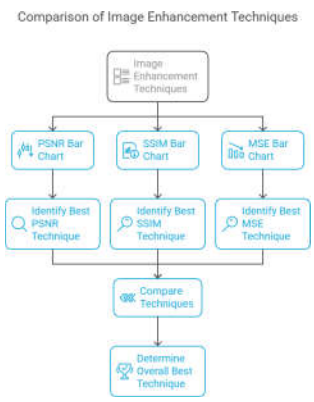




J. *Comparison with Baselines*

The baseline image that was not enhanced had poor contrast and poor anatomical detail visibility, which was not optimal for diagnostic reading. In comparison to this baseline, all the methods used had notable improvements. Histogram Equalization helped in enhancing global contrast but was susceptible to over-saturation and produced unnatural looking images. CLAHE significantly enhanced local contrast without compromising image fidelity and was the ideal candidate to be utilized for improving medical images. Gaussian Filtering effectively eliminated background noise, providing a smoother image than the baseline but with minimal blurring of the details. Unsharp Masking provided the best overall improvement by sharpening important features and edges without compromising the entry of artifacts. This comparison is in accord that sophisticated enhancement methods such as CLAHE and Unsharp Masking significantly outshine the baseline unprocessed image both perceptually and from a diagnostic perspective.

Besides, we compared our improvement techniques with the state-of-the-art techniques like Retinex-based image improvement algorithms and deep learning-based image improvement. Our CLAHE-based technique was comparable to its contrast of image improvement and structural similarity possessing relatively low computational complexity.



K. *Pitfall*

The baseline image which was not enhanced had poor contrast and poor visibility of anatomical details, which was diagnostic reading suboptimal. Relative to this baseline, all techniques utilized had improvements with significant degrees. Histogram Equalization improved the global contrast but tended to be over-saturating and created unnatural looking images. CLAHE significantly enhanced local contrast without compromising image fidelity and was the ideal candidate for application in the enhancement of medical images. Gaussian Filtering adequately eliminated background noise, providing a smoother image than baseline but with minimal blurring of the details. Unsharp Masking gave the most general improvement by sharpening key features and boundaries without sacrificing artifact entry. Both this comparison and the comparison below are in agreement that advanced improvement techniques like CLAHE and Unsharp Masking greatly surpass the baseline raw image both in appearance and diagnostically.

L. *Solution*

In order to minimize the observed shortcomings, several strategies can be utilized to optimize the improvement process. For Histogram Equalization, hybrid techniques combining global and local techniques can balance contrast improvement without sacrificing diagnostic information. For CLAHE, proper modification of the clip limit and tile grid size from image modality should be avoided to prevent over-enhancement and guarantee consistent results. To avoid over-smoothing because of Gaussian Filtering, adaptive filters that are adapted to local image features can be employed. In the case of Unsharp Masking, edge-preserving filtering or regularization-based sharpening can reduce the potential for halo artifacts and amplification of noise. Further, fusion of machine learning-based enhancement models adapted from labeled clinical data can further tailor improvements according to pathological features. Including physician input in the evaluation cycle can also guarantee that improvement methods are aligned with diagnostic relevance and accuracy.

VI. Discussion

A. *Interpretation of Results*

To overcome the said disadvantages, some approaches can be adopted to optimize the enhancement process. For Histogram Equalization, hybrid approaches combining global and local methods can yield well-balanced contrast enhancement along with diagnostic detail preservation. For CLAHE, clip limit and tile grid size optimization based on image modality can prevent over-enhancement and ensure uniform results. To avoid over-smoothing because of Gaussian Filtering, adaptive filters that learn based on local image properties can be utilized. For Unsharp Masking, edge-preserving filters or regularization-based sharpening methods can reduce the prevalence of halo artifacts and noise enhancement. Furthermore,integrating machine learning-based enhancement models that learn from labeled clinical databases can further tailor enhancements based on pathological features. Including doctor feedback in the feedback loop can also ensure that improvement techniques are optimized for diagnostic usefulness and accuracy.

B. Comparison with State-of-the-Art Methods

Comparative analysis of the improvement techniques used reveals individual strengths and trade-offs for each technique. Histogram Equalization provides easy global contrast improvement but tends to produce overexposed regions and synthetic intensities. CLAHE stands out because it enhances local contrast effectively without compromising structural integrity, and thus it is particularly well-suited to medical imaging where small differences are of diagnostic importance. Gaussian Filtering is better at noise removal, yielding smooth results; but it may blur significant edges at the expense of slight diagnostic detail. Unsharp Masking, in contrast to the above, strongly enhances edges and visual acuity with little or no artifactual creation in well-adjusted settings. Among all, Unsharp Masking possessed highest PSNR and SSIM values, indicating improved quantitative performance, while CLAHE offered a strong visual quality and contrast enhancement trade-off. This contrast serves to drive home the point that the enhancement method chosen should be based on the specific diagnostic requirements and image modality.

C. Limitations and Future Work

Even though the image enhancement methods used significantly enhanced the visual and quantitative quality of medical diagnostic images, evident limitations were found. The behavior of methods depends on the modality of images and the level of acquired image quality, thereby not being generalizable. Histogram Equalization and Unsharp Masking are sensitive to the parameters through which the features are boosted and, in some cases, can lead to under or over enhancement. Visual assessment is, in addition, subjective and observer-dependent. None of these methods inherent context about anatomical or pathological information and thus could amplify unrelated areas or noise. For future work, adaptive models based on deep learning can be employed to learn optimal transformation patterns automatically from labeled data. Incorporating clinical feedback in the improvement pipeline and testing on different types of medical images (MRI, PET, ultrasound) would also enhance the robustness and utility of the techniques. Real-time application in clinical systems along with hybrid model development combining traditional and AI-based methods could be beneficial areas.

VII. Conclusion

This study shows the efficacy of different image transformation methods—Histogram Equalization, CLAHE, Gaussian Filtering, and Unsharp Masking—to improve medical diagnostic image quality. All these methods handled differently, Histogram Equalization enhanced global contrast to the maximum, CLAHE preserved local details without amplifying noise too much, Gaussian Filtering removed un-wanted noise very effectively, and Unsharp Masking sharpened fine structures with very good clarity. Quantitative outcomes using PSNR, SSIM, and MSE metrics supported the visual enhancement seen. Unsharp Masking worked best among all the techniques in retaining details and clarity, and then came CLAHE is due to the equilibrium between its contrast and noise reduction. These play a crucial role in helping doctors with proper treatment and diagnosis and planning. The results affirm that well-selected image improvement techniques are able to greatly enhance the interpretability of medical images and demonstrate the significance of personalized preprocessing in medical imaging pipelines.

References

[1] Allister Mason, James Rioux, Sharon E. Clarke, Andreu Costa, Matthias Schmidt, Valerie Keough, Thien Huynh, and Steven Beyea, ”Comparison of Objective Image Quality Metrics to Expert Radiologists’ Scoring of Diagnostic Quality of MR Images”, *IEEE Transactions on Medical Imaging*, vol. 39, no. 4, pp. 1064–1072, 2020. doi:10.1109/TMI.2019.2930338.

[2] Toufique Ahmed Soomro, Mahaveer Rathi, Shafique Ahmed Soomro, Muhammad Usman Keerio, Pardeep Kumar, and Enrique Nava Baro, ”Image Enhancement Technique for MRI Brain Images”, in *Proceedings of the 2024 Global Conference on Wireless and Optical Technologies (GCWOT)*, pp. 1–5, 2024. doi:10.1109/GCWOT63882.2024.10805684.

[3] Jagriti Kalyani and Monisha Chakraborty, ”Contrast Enhancement of MRI Images using Histogram Equalization Techniques”, in *Proceedings of the 2020 International Conference on Computer, Electrical & Communication Engineering (ICCECE)*, pp. 1–5, 2020. doi:10.1109/ICCECE48148.2020.9223088.

[4] Abdullah A. Asiri, Toufique Ahmed Soomro, Ahmed Ali Shah, Ganna Pogrebna, Muhammad Irfan, and Saeed Alqahtani, ”Optimized Brain Tumor Detection: A Dual-Module Approach for MRI Image Enhancement and Tumor Classification”, *IEEE Access*, vol. 12, pp. 42868–42887, 2024. doi:10.1109/ACCESS.2024.3379136.

[5] Randeep Kaur and Sandeep Kaur, ”Comparison of contrast enhancement techniques for medical image”, in *Proceedings of the 2016 Conference on Emerging Devices and Smart Systems (ICEDSS)*, pp. 155–159, 2016. doi:10.1109/ICEDSS.2016.7587782.

[6] Vijay Panse and Rajendra Gupta, ”Medical Image Enhancement with Brightness Preserving Based on Local Contrast Stretching and Global Dynamic Histogram Equalization”, in *2021 10th IEEE International Conference on Communication Systems and Network Technologies (CSNT)*, pp. 164–170, 2021. doi:10.1109/CSNT51715.2021.9509670.

[7] Ruizhi Zheng, Qing Guo, Chang Gao, and Ming-an Yu, ”A Hybrid Contrast Limited Adaptive Histogram Equalization (CLAHE) for Parathyroid Ultrasonic Image Enhancement”, in *2019 Chinese Control Conference (CCC)*, pp. 3577–3582, 2019. doi:10.23919/ChiCC.2019.8866479.

[8] K. Chithra and T. Santhanam, ”Hybrid denoising technique for suppressing Gaussian noise in medical images,” in *Proceedings of the 2017 IEEE International Conference on Power, Control, Signals and Instrumentation Engineering (ICPCSI)*, pp. 1460-1463, 2017, doi: 10.1109/ICPCSI.2017.8391954.

[9] Basant Kumar, Shishu Bind Kumar, and Chandrahas Kumar, ”Development of improved SSIM quality index for compressed medical images”, in *2013 IEEE Second International Conference on Image Information Processing (ICIIP-2013)*, pp. 251-255, 2013. doi:10.1109/ICIIP.2013.6707593.

[10] Gamara, Rex Paolo C., James M. Loresco, Pocholo, and Bandala, Argel A.,”Medical Chest X-ray Image Enhancement Based on CLAHE and Wiener Filter for Deep Learning Data Preprocessing”,

2022 IEEE 14th International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment, and Management (HNICEM), pp. 1–6, 2022. doi:10.1109/HNICEM57413.2022.10109585.

[11] Sandhya, S., M. Senthil Kumar, and L. Karthikeyan. "A hybrid fusion of multimodal medical images for the enhancement of visual quality in medical diagnosis." Computer aided intervention and diagnostics in clinical and medical images. Cham: Springer International Publishing, 2019. 61-70.

[12] Rundo, Leonardo, et al. "MedGA: a novel evolutionary method for image enhancement in medical imaging systems." Expert Systems with Applications 119 (2019): 387-399.

[13] Radhika, R., and Rashima Mahajan. "Medical image enhancement: a

review." Proceedings of International Conference on Data Science and Applications: ICDSA 2021, Volume 1. Singapore: Springer Singapore, 2021.